Journal of
Knowledge Economy Studies

https://kes.hmu.ac.ir

Hazrat-e Masoumeh University

Turbulence as a Double–Edged Sword: The Moderating Role of I4.0 Technologies in the Frugal Innovation–New Product Development Performance Link

Article Type:
Research Article

Hossein Shirazi[1*]
Department of Technology Management, Qom Branch, Islamic Azad University, Qom, Iran
Corresponding Author
E-mail: hosseinshirazi@iau.ac.ir

Hossein Bakhtiari[2]
Department of Management, Faculty of Economic and Administrative Sciences, University of Qom, Qom, Iran
E-mail: h.bakhtiari.ac@gmail.com

Received: 14 June 2026
Revised: 25 August 2026
Accepted: 26 August 2026
Available Online: 01 October 2026

Abstract

New product development (NPD) is a strategic tool for firms to compete, differentiate themselves, and outperform competitors, yet NPD remains a key organizational challenge. This study examined the impact of frugal innovation (FI) on new product development performance (NPDP) within the small household electrical appliances (SHEA) sector. Additionally, it explored the moderating roles of Industry 4.0 (I4.0) technologies and technological turbulence (TT) in linking FI to NPDP. Grounded in the Resource–Based View (RBV), Human–Organization–Technology (HOT) framework, and Schumpeterian innovation theory, this research, from a paradigmatic perspective, fell under post–positivism. In terms of approach and reasoning, the study followed a quantitative–deductive approach, and from the perspective of method and nature, it employed a descriptive survey design. Data were collected from 111 senior managers in the Iranian SHEA industry, exceeding the minimum required sample size of 108, as determined by G*Power analysis. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS–SEM) via Smart–PLS 4 software. The results confirmed that FI significantly and positively influenced NPDP. Furthermore, the study found that I4.0 technologies strengthen this relationship by enabling precise engineering, rapid prototyping, and cost–effective production, thus enhancing the benefits of FI under varying technological conditions. Technological turbulence also moderated the impact of I4.0, amplifying the positive effects on NPDP by fostering organizational agility and responsiveness to rapid change. The importance–performance map analysis highlighted I4.0 adoption as a critical area for managerial focus to sustain competitive advantages. These findings advanced the theoretical understanding of innovation management by clarifying the interplay between frugal innovation, Industry 4.0 technologies, and technological turbulence, enriching the understanding of their joint effects on NPDP. From a practical perspective, the results guide managers in resource allocation and strategic adoption of digital technologies to enhance innovation outcomes amid technological turbulence, thereby supporting sustained competitive advantages in resource–constrained and dynamic market environments.

Keywords

Frugal Innovation, New Product Development Performance, Technological Turbulence, Industry 4.0 Technologies, Important–Performance Map Analysis, Smart–PLS 4.

Cite this article: Shirazi, H. & Bakhtiari, H. (2026). Turbulence as a Double–Edged Sword: The Moderating Role of I4.0 Technologies in the Frugal Innovation–New Product Development Performance Link. *Journal of Knowledge Economy Studies (JKES)*, 3(3), 65-94. DOI: http//doi.org/10.22034/kes.2026.2091637.1114

Authors retain the copyright and full publishing rights.
Online ISSN: 3060-7329
Publisher: Hazrat-e Masoumeh University.

Introduction

In today's volatile business landscape, firms must improve their new product development (NPD) processes to stay competitive and survive over time. NPD helps companies stand out and beat their rivals (Knudsen et al., 2023). Nevertheless, the conditions that make NPD successful are not the same everywhere. In markets where resources are limited, traditional innovation models—which often require substantial financial investment and target wealthy customers—face serious challenges. These challenges have pushed researchers and managers to explore alternative approaches to innovation. One such approach is frugal innovation (FI). FI focuses on cutting costs, using fewer resources, and delivering only what customers really need (Fransisca et al., 2025). Yet how exactly FI affects NPD performance is still not well understood. It likely depends on other factors that have not been fully explored.

The concept of frugal innovation (FI) originates from the base of the pyramid (BOP), a setting characterized by extreme resource scarcity. The limitations concern the ability to develop and produce products at affordable costs, experts argue. The main limitations are lack of institutional restrictions, scarcity of resources and low disposable income of consumers (Bas, 2020). However, the limitations provide fertile ground for innovation and new product development, say academics. It is critical to understand the market and consumer needs and the current and potential limitations in the FI environment. Failure to consider these requirements and limitations may result in unsuccessful implementation of the product due to the unmet expectations of consumers and imbalance of the product features (Ukbaeva et al., 2026).

The sectors and markets are increasingly disrupted by environmental changes driven by the Industry 4.0 (I4.0) phenomenon, driven by innovations in products, processes, and business models. With rapid technological change, organizations must understand how to develop new products and/or process improvements using emerging technologies (Wijewardhana et al., 2021). Emerging I4.0 technologies are increasingly being integrated into various applications and sectors, enabling firms to achieve competitive advantages through digital transformation (Ardito et al., 2019). However, the implementation of I4.0 is still in the initial phase of development and limited to certain sectors and applications (Wijewardhana et al., 2021). Moreover, manufacturing companies have to face the challenge of improving their new product development processes especially in markets with the need for innovation, shorter time–to–market, product variety and higher quality (Tiedemann et al., 2020). Previous studies have emphasized the core values of Industry 4.0, such as interoperability, information transparency, technical support, and decentralized decision–making, along with their implementation with relevant technologies. These developments have paved the way for some manufacturing plants, thereby providing firms with a competitive advantages in modern operations (Wijewardhana et al., 2021).

Furthermore, technological turbulence (TT) refers to the complexity, uncertainty, and unpredictability of technological change (He & Wu, 2024). The dominant logic underlying the adoption of I4.0 technologies to foster NPD is that such technologies enable

enterprises to identify new opportunities, update organizational routines, and achieve technological breakthroughs through resource reconfiguration. Under conditions of high TT, firms equipped with I4.0 technologies become more responsive to technological shifts and can rapidly restructure their internal processes (Fiorini et al., 2025), which may further enhance NPD performance (NPDP). The impact of environmental turbulence is particularly pronounced in the form of amplifying idle technologies by increasing the need to reconfigure existing technologies and capabilities in order to develop new technologies with improved external alignment (Sinaga et al., 2019).

Although FI, I4.0, and TT have each been studied separately, very little is known about how they might work together. FI e emphasizes achieving greater value with fewer resources. I4.0 offers tools that can help firms design and produce more efficiently. TT increases the pressure on firms to adapt rapidly to technological change. It is reasonable to ask whether the combination of these factors could produce a stronger effect on NPD performance than any single factor alone. For example, having I4.0 capabilities may help a firm turn its frugal ideas into products faster and at lower cost. However, the extent of these benefits may depend on how fast technology is changing around the firm. In a turbulent environment, digital tools may be more useful because firms need to respond quickly. In a stable environment, the same tools may add less value. Taken together, these arguments suggest that the impact of FI on NPD may be shaped by both I4.0 adoption and technological turbulence together. However, empirical research has not yet tested this possibility. Nevertheless, despite the growing body of research on FI and on I4.0 technologies, a significant gap remains. Existing studies have examined FI's impact on firm performance in isolation, or have explored I4.0's direct effects on NPD efficiency. However, scant empirical attention has been paid to how I4.0 technologies might moderate the FI–NPDP relationship, and even less is known about how this moderating effect itself is contingent upon the level of technological turbulence (TT) in the environment (i.e., a moderated–moderation model). This study addresses this gap by developing and testing a three–way interaction model in the context of the Iranian SHEA industry. Accordingly, this study seeks to address the following research questions:

Research Question 1: Does FI influence NPDP?

Research Question 2: What roles do I4.0 technologies and TT play in transforming FI into NPDP?

These research questions are directly anchored in three theoretical pillars: Resource–Based View (RBV), which frames FI as a valuable, rare, and inimitable capability; the Human–Organization–Technology (HOT) readiness framework, which positions I4.0 as a synergistic enabler; and Schumpeterian innovation theory, which explains how TT disrupts equilibrium and demands dynamic reconfiguration. The moderated–moderation framework addressed in RQ2 advances theory by showing that the FI–NPDP link is not universal but contingent on digital readiness (I4.0) and environmental dynamism (TT).

The remainder of this article is structured as follows: Section 2 presents the literature

review and theoretical background; the methodology is described in section 3; Section 4 presents the results. Some suggestions conclude section 5.

Literature review and hypotheses development

Underpinning theories

This study draws on three theoretical perspectives to support the conceptual model:

First, the Resource-Based View (RBV) holds that sustainable competitive advantages arises from resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Based on this theory, researchers have connected critical resources and technological capabilities to superior new product development performance (NPDP) (Qin, 2024). Second, this study adopts the Human–Organization–Technology (HOT) readiness framework (Yusof et al., 2008), which suggests that the synergistic alignment among human factors (e.g., user satisfaction), organizational factors (e.g., structure), and technological factors (e.g., system quality) determines how effectively a technology is utilized (Kumar & Bhatia, 2021). Within this framework, I4.0 serves as the core technology, offering the mechanisms necessary to build and sustain competitive advantages in product offerings (Aqmala et al., 2025). Nevertheless, I4.0 readiness alone does not directly enhance firm performance; rather, its impact is mediated through value creation in key business processes such as NPD (Stentoft et al., 2020). Accordingly, I4.0 capabilities can become a source of competitive advantages by forming a specialized, difficult–to–imitate competence that strengthens the NPD process. This effectively positions the effective deployment of technological tools as a core NPD competence, leading in turn to competitive gains (Kumar & Bhatia, 2021). Third, the theoretical foundation is further grounded in the Schumpeterian perspective on innovation strategy, where firms deliberately invest resources in innovative activities to renew their capabilities and disrupt market equilibrium (Dosi et al., 2000). Schumpeter's economic conceptualization of innovation is central to this paper, as it frames innovation not as a marginal adjustment but as a dynamic force that propels economic development by replacing existing methods and generating new market realities (Schumpeter, 1912/2002). Each of these three theories serves a distinct yet complementary role in supporting the research hypotheses. RBV provides the foundation for H1 by framing FI as a valuable, rare, and inimitable capability that, when embedded in NPD processes, yields performance advantages that competitors cannot easily replicate (Barney, 1991). The HOT readiness framework underpins H2 by suggesting that I4.0 technologies function as a synergistic enabler—not as a direct driver of performance, but as a contingency factor that amplifies the effect of FI on NPDP when human, organizational, and technological elements are aligned (Stentoft et al., 2020; Yusof et al., 2008). Finally, Schumpeterian innovation theory supports H3 by explaining that TT disrupts existing equilibrium and compels firms to reconfigure their resource bases. Under such conditions, the moderating effect of I4.0 on the FI–NPDP relationship becomes stronger because turbulent environments heighten the value of digital capabilities for rapid adaptation and creative destruction (Dosi et al., 2000;

Schumpeter, 1912/2002). Thus, these three theoretical perspectives collectively justify a moderated–moderation model in which the effect of FI on NPDP is not universal but conditional upon both internal digital readiness (I4.0) and external environmental dynamism (TT).

Frugal innovation (FI)

Frugal innovation (FI) traces its conceptual origins to the Indian notion of jugaad—a term describing low-cost solutions designed for the bottom of the pyramid (BOP). Over time, FI has garnered increasing recognition worldwide, extending its relevance beyond emerging economies into developed markets as well (Vesci et al., 2021). FI serves a dual purpose: it offers a viable strategy for operating under resource constraints, while simultaneously enhancing the quality of life for BOP consumers (Iqbal & Piwowar-Sulej, 2023).

The intellectual foundations of FI can be traced to Schumacher's (1973) "Appropriate Technology" movement. Schumacher advocated technologies that were labor-intensive, easy to operate and maintain, affordable for low-income users, small in scale, and environmentally benign—viewing them as a means of alleviating poverty. The modern conception of FI, which gained traction in the late 2000s, essentially reinterprets appropriate technology within a for-profit paradigm. This reframing underscores the central role of the private sector as both an engine of economic activity and an agent of development (United Nations, 2015). FI, therefore, extends well beyond serving low-income markets; it challenges established innovation frameworks by advocating for a fundamental rethinking of production processes and business models. Nonetheless, its primary focus remains on addressing the needs of low-income and emerging middle-income consumers and producers in developing economies (Rosca et al., 2018). FI pursues this objective by promoting affordable products that incorporate only essential features, thereby catering to the demands of resource-constrained consumers (Iqbal et al., 2025).

Within resource-scarce environments, FI manifests through three complementary approaches: bricolage, which responds to material shortages; improvisation, which addresses time constraints; and FI itself, which accommodates the absence of affluent consumers (Dost et al., 2019). Drawing on the existing literature, Weyrauch and Herstatt (2017) identify several defining characteristics of FI: a focus on essential functionality, substantially lower purchase and ownership costs, reduced consumption of material and financial resources, user-friendliness, robustness, high value and quality, scalability, and sustainability.

Given its emphasis on resource efficiency, inclusion of low-income actors, and collaborative orientation, FI has considerable potential to contribute to sustainable development (Knorringa et al., 2016). Wimschneider et al. (2020) argue that three conditions are necessary for FI to drive inclusive development: first, the successful commercialization of affordable products and services; second, the meaningful participation of low-income actors in value chains; and third, the frugal utilization of natural resources. Although FI is commonly perceived simply as low-cost innovation, it encompasses far more than mere cost reduction. Rather, FI operates on the principle of simplification, striving for less rather than more through the strategic deployment of intelligent technology (Ukbaeva et al., 2026).

FI and NPDP

NPD is defined as the process of bringing a new product to market through ideation, screening, testing, and final customer approval. NDP is central to a firm's long–term success and competitive advantages, exerting significant influence over the entire value chain and key strategic decisions concerning quality, cost, and time (Wijewardhana et al., 2021). In contemporary business environments, NPD functions as a strategic tool for differentiation and growth. Accordingly, its performance—measured in terms of operational effectiveness in quality, timeliness, and customer responsiveness—represents a critical determinant of sustained organizational success (Ukbaeva et al., 2026). The NPD environment is gradually evolving with the emergence of new markets that have become core innovation hubs due to their huge market size, increasing demand and rich R&D expertise (Agarwal & Brem, 2012). One of the key trends in these regions is the increasing consumer preference for low–priced goods and services. This demand stems from the core characteristics of frugal offerings: they deliver essential functionalities and robust quality at substantially lower costs by radically minimizing resource usage throughout the value chain (Awwad & Akroush, 2013). In this context, FI may improve the organization's efficiency by generating novel ideas under tight constraints and frequently offering significant improvements in product performance without raising costs (Lim & Fujimoto, 2019). In this regard, the development of new ideas, however, requires an in–depth knowledge of the lifestyles, needs and challenges of the users and end users. FI encourages creative innovation across four key dimensions: awareness, affordability, accessibility, and availability. FI refers to the creation of a product despite limited resources. It has several advantages that cannot be achieved by traditional product development methods (Ukbaeva et al., 2026). Therefore, the FI framework provides a complementary and strategic strategy to the NPD process in line with the conditions of resource–constrained environments and value–seeking consumers in emerging and international markets. By compelling firms to focus on essential functionalities, minimize unnecessary resource use, and reduce costs while maintaining acceptable quality, FI can enhance firms' ability to develop products that meet the needs of resource-constrained consumers. This capability, when embedded in the NPD process, enables firms to differentiate their offerings and achieve superior performance outcomes unattainable through conventional product development approaches (Ukbaeva et al., 2026). Accordingly, we hypothesize:

H1: FI affects NPDP.

The moderating role of Industry 4.0 technologies

Industry 4.0 (I4.0) represents an important industrial revolution and originated as a German strategic initiative aimed at enhancing the competitiveness of manufacturing. This industrial revolution is characterized by the technological amalgamation of Cyber–Physical Systems, the Internet of Things, and digital services across manufacturing and logistics systems, radically transforming value generation, business frameworks and organizational structures (Stentoft et al., 2021). I4.0 is characterized by a range of technological features

that provide real time data of different processes and applications in organizational environments, facilitating a better understanding of actual operational conditions, breakdowns and possible improvements, etc. Furthermore, I4.0 applications can improve self–awareness and productivity and provide deeper insights for decision–making (Ardito et al., 2019). This digital paradigm equips enterprises with the infrastructure and intelligence necessary for next–generation production, management, and smart product development (Wijewardhana et al., 2021). For manufacturing firms—particularly those under pressure to accelerate time–to–market, improve product quality, and manage product diversity—I4.0 technologies provide critical capabilities for revolutionizing core processes such as NPD. Advanced technologies like virtual and augmented reality can foster collaboration and efficiency throughout the NPD lifecycle. Within a smart manufacturing context, advanced I4.0 technologies can therefore enhanceimprovements in the NPD process (De Silva et al., 2019). Firms that fail to understand and bridge the gap toward I4.0 readiness risk significant competitive disadvantages in terms of customer satisfaction and cost efficiency (Wijewardhana et al., 2021).

From a different perspective, the FI paradigm addresses a different market imperative: creating high–value products at drastically reduced costs to serve price-sensitive and resource-constrained consumers, particularly in emerging markets (Lim & Fujimoto, 2019). FI achieves "more with less" by focusing on core functionalities and employing innovative engineering approaches,often through the simplification or elimination of non–essential features, to substantially reduce the cost of an existing product or technology without compromising acceptable quality. Hence, there is a need to radically rethink and redesign business processes in organizations to absorb the new wave of technological changes. Importantly, these two paradigms are not mutually exclusive; rather, they can be powerfully synergistic within the NPD process (Lim et al., 2020). I4.0 provides advanced digital toolkit—including smart, connected technologies and data–driven processes—that can be intentionally applied to simplify, streamline, and cost–optimize product design and manufacturing (Ukbaeva et al., 2026). In general, making an existing I4.0–based smart product "frugal" for new markets requires a tailored application of these very technologies to lower costs (Iqbal et al., 2025). This suggests that I4.0 capabilities can moderate the relationship between FI and NPD performance. In essence, a firm's proficiency with I4.0 can amplify the effectiveness of its FI efforts. It can enable more precise engineering, rapid prototyping, and efficient, low–waste production, thereby allowing the firm to achieve the radical cost reductions and robust quality targets of FI more successfully and integrate them into high–performing NPD outcomes. In essence, I4.0 technologies provide the digital infrastructure—such as real–time data analytics, smart manufacturing, and rapid prototyping—that can systematically reduce the costs and time associated with frugal product development. Without such infrastructure, FI efforts may remain limited in scale and efficiency. With it, firms can more effectively translate frugal design principles into marketable products that meet both cost and quality targets. Therefore, I4.0 technologies are expected to moderate the relationship between FI and NPDP. Formally stated:

H2: I4.0 technologies play a moderating role in the impact of FI on NPDP.

The moderating role of technological turbulence (TT)

One of the many factors affecting environmental uncertainty that is particularly important is turbulence, or the speed and unpredictability of change (Duncan, 1972). Technological turbulence (TT) refers to the rate of technological change and the rate of unpredictability of technological change in product development in an industry (Jaworski & Kohli, 1993), and is a significant environmental factor for new product development (NPD) teams. Increased TT can change industry benchmarks, thus making prediction difficult (Chen et al., 2015). There is more uncertainty in turbulent environments than in stable environments, and timely information is needed to improve decision–making (Wu et al., 2005). The large information requirement means that a large information processing capacity is needed; hence, high TT requires appropriate organizational structures. Organizational resources may not be reallocated in response to changes in the technological landscape (Song & Montoya–Weiss, 2001). A capacity or resource that was an asset in the past may become a liability if it no longer fits the purpose. Thus, technological progress is viewed as both beneficial and harmful (Chen et al., 2015). Contingency theory suggests that organizations are constantly interacting with their environment and must change their ways and characteristics to fit different environmental conditions (Burns & Stalker, 1961; Lawrence & Lorsch, 1967). Fluid and chaotic environments force organizations to make major innovations (Cooper, 2017). An example is the digital transformation of industrial enterprises (Obradović et al., 2021). Innovation is the best way to deal with instability in external contexts. Thus, companies are able to adapt and develop new products according to the growing needs of consumers (Fiorini et al., 2025). In highly competitive markets, firms' innovation efforts are driven by the constant and rapid changes in consumer demands and preferences (Tsai & Yang, 2013). The features of FI are therefore changing. Economical products are different because they include innovations sometimes through creative adaptation or reengineering of existing products. Hence, these changes compel firms to alter the ways in which they produce their products (Kumar & Bhatia, 2021). Economical products often have a short life span, as they are typically redesigned or adapted from existing products (Lim et al., 2020).

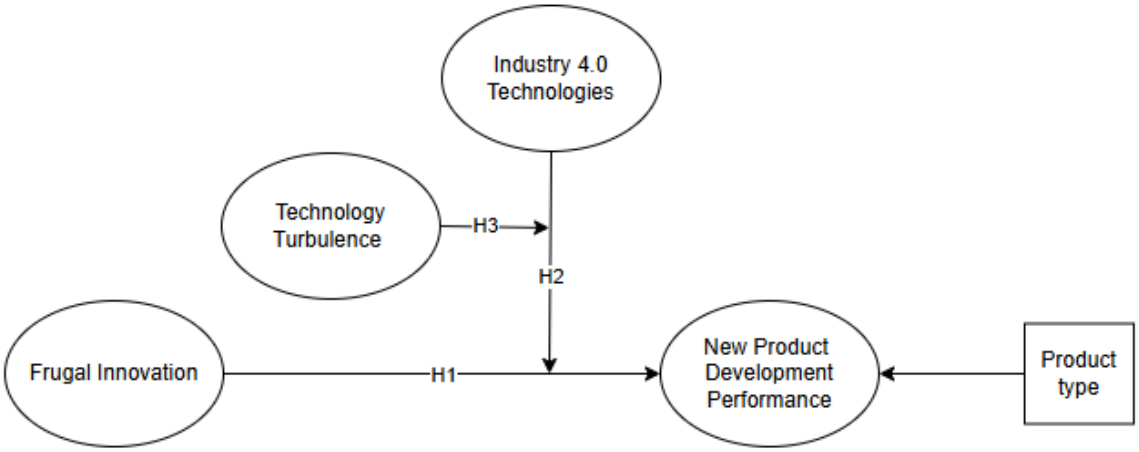
The logic for the three–way interaction (TT × I4.0 × FI) rests on the premise that the value of I4.0 capabilities in amplifying FI's effect on NPDP is not constant across all environmental conditions. Under high TT, where technologies change rapidly and unpredictably, firms face strong pressure to reconfigure their resources and update their processes continuously (Fiorini et al., 2025). In such environments, I4.0 technologies become especially valuable because they enable firms to quickly sense technological shifts, adapt their frugal product designs, and respond to emerging market demands. Conversely, under low TT, the environment is relatively stable, and the additional advantage provided by I4.0 capabilities diminishes because the need for rapid reconfiguration is less urgent. This differential value of I4.0 capabilities across levels of TT implies that the moderating effect of I4.0 on the FI-NPDP relationship is itself

moderated by TT. Thus, we hypothesize:

> **H3:** TT moderates the impact of I4.0 technologies on the nexus between FI and NPDP.

Based on the stated materials, the research model is presented in Figure 1.

Figure 1.
The Research Conceptual Model



(Source: The Researcher's Findings)

Methodology

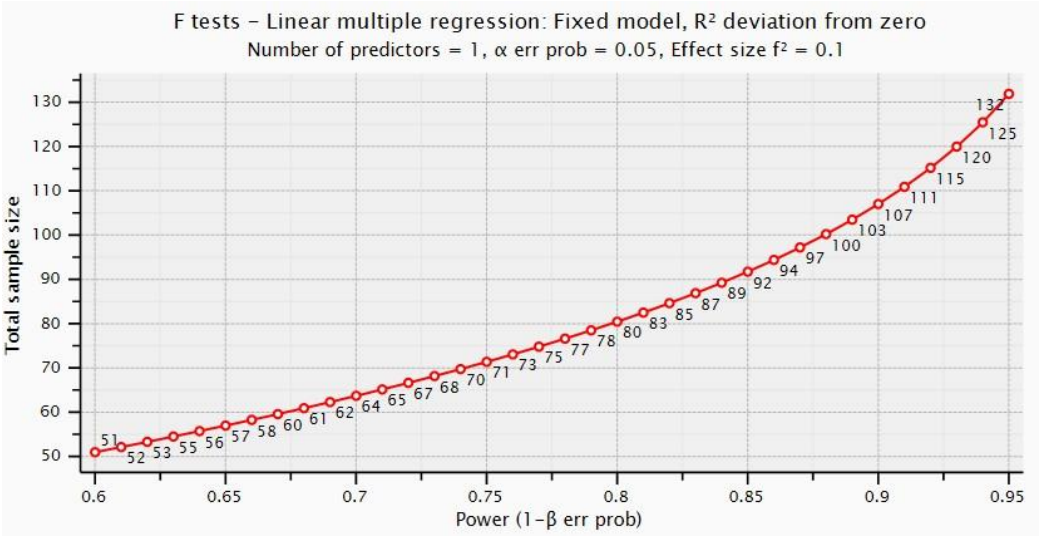
Methodologically speaking, this study adopts a post-positivist stance and falls under the umbrella of quantitative research, employing a deductive reasoning approach along with a survey-based strategy.

Target population and sample size

The sector of small household electrical appliances (SHEA) in Iran is one of the accelerating factors in industrial development. This industry is highly diverse, featuring a wide range of applications. Beyond meeting essential domestic needs, it has recently expanded into administrative and commercial areas, thereby attracting significant capital investment (Safardoust et al., 2023). Accordingly, the empirical setting chosen to test the conceptual model and its hypotheses is the SHEA sector, a choice justified by two principal considerations. First, because importing household appliances into Iran is prohibited, domestic manufacturers face intense competitive pressures, which compel them to introduce new products to the market continuously. Second, under such competitive conditions, these firms are persistently seeking ways to lower the production costs of new offerings while simultaneously either enhancing or at least preserving product quality, all in an effort to secure a competitive edge. With this context in mind, the target population comprised senior managers operating within the SHEA industry. These respondents were selected based on their strategic decision-making roles and comprehensive understanding of their firms' new product development performance. To ensure the clarity of the sampling procedure, the following details are specified. The sampling frame consisted of a list of senior managers

(including R&D managers, production managers, marketing managers, sales managers, factory managers, and firm owners) from active manufacturing firms in the Iranian SHEA industry, as registered with the Iranian Household Appliances Manufacturers Association. The inclusion criteria required that respondents (1) hold a position at the senior management level or above, (2) have been directly involved in at least one NPD project that had been commercially launched for a minimum of six months before data collection, and (3) have worked in their current organization for at least three years. The required sample size was calculated using G*Power software, yielding 108 respondents. To improve the generalizability of the findings, simple random sampling was applied to this list (Sarstedt et al., 2018).

Figure 2.
Determining Sample Size with G*Power



(Source: The Researcher's Findings)

Model variables

Within the research model, each variable serves a distinct functional role: FI functions as the independent variable, NPDP as the dependent variable, and both I4.0 technologies and TT as moderating variables.

To account for contextual factors that could potentially influence the results, product type was incorporated as a control variable. Product type constitutes a significant contextual factor capable of shaping NPD practices and outcomes. Following the innovation typology proposed by Chen et al. (2015), this variable was operationalized by coding innovations as either incremental (0) or non-incremental (1). Although the study focuses on the SHEA industry, the relationship between products and I4.0 may vary among different firms.

Data collection

Data were collected through a standardized questionnaire, in which each latent construct was measured using multiple indicator items on a five-point Likert scale anchored at 1 (strongly disagree) and 5 (strongly agree). Table 1 provides a concise overview of the measurement instruments employed in this study.

The research instrument comprises a general section designed to gather demographic information. Among the valid respondents, the sample composition is as follows: 33 sales managers (30.55%), 25 marketing managers (23.14%), 22 R&D managers (20.37%), 19 production managers (17.59%), 6 factory managers (5.55%), and 3 firm owners (2.77%). Consequently, all respondents are department heads or senior managers with substantial familiarity with the questionnaire's subject matter. The specialized portion of the questionnaire was pre-tested with both industry practitioners and academic experts; their feedback informed iterative refinements to enhancethe instrument's reliability and content validity.

Table 1.
The Questionnaire Structure

Variables	Role	Items	Summary of Questions	Sources
FI	Independent	1–5	using environmentally friendly materials in new ways; considering the impact of product manufacturing on the environment and the world; using data analysis to identify trends; considering different customer segments when producing products; using up-to-date technologies to reduce production costs and increase cost-effectiveness.	(Aqmala et al., 2025)
I4.0 tech	Moderator	6–13	Customer specifications; Competitors use the latest digital innovations; To keep costs down; To speed up time to market; As per statutory obligations/revised laws; Shortage of skilled labor; Initiatives undertaken with the contribution of the public advisory framework (incubators, local enterprise assistance); An intentional approach to emerging digital technologies.	(Stentoft et al., 2021)
NPDP	Dependent	14–18	A key source of revenue for the company; Excellence in product development; Continuous improvement in development processes over time; Greater innovativeness compared to competitors in products; Consistent achievement of development goals.	(Li et al., 2024)
TT	Moderator	19–22	Technology used in our sector changes rapidly; Technology used in this product changes rapidly; Technology changes in the sector generate many new product ideas; Technology changes in the sector create major opportunities.	(He & Wu., 2024)

(Source: The Researcher's Findings)

The survey administration took place over a three–month window, running from January through March 2026. A total of 250 questionnaires were distributed via email, and after repeated follow-ups, 111 of them were considered usable due to completeness and acceptance. The final response rate was 44%, which aligns with acceptable benchmarks in survey research (Sekaran & Bougie, 2016).

Common method bias (CMB)

Common method bias (CMB) represents a major challenge when data collection is conducted through questionnaires. Issues related to CMB must be addressed to ensure that respondents provide genuine feedback. Several measures were taken to minimize potential CMB. Several measures were taken to minimize potential CMB. First, we employed Harman's single-factor test, which explained only 29% of the total variance,

indicating that CMB is not a concern (Podsakoff et al., 2003). Additionally, the questionnaire was designed such that items for the independent construct appeared before those for the dependent variable (Yadlapalli et al., 2018). Respondents were also assured of the anonymity of their responses and that the data would be used solely for academic purposes. The instructions clarified that there are no correct answers and encouraged respondents to rely on their knowledge rather than emotions (Podsakoff et al., 2003). Participants were asked to provide responses regarding a recent, completed, and well–known NPD initiative. To minimize bias against more successful initiatives, the standards of recency and familiarity were used. Only those initiatives that had been commercially launched for at least six months were eligible, so that participants were making informed performance evaluations. Finally, the answers were checked for completeness and patterns to detect potential response bias or inattentive responses.

Data analysis technique

The study employs Partial Least Squares (PLS) for hypothesis testing. PLS is particularly suitable for studies with relatively small sample sizes and is effective in testing complex models (Davari & Rezazadeh, 2013). It is also recommended for emerging research fields where theory is still developing, and the focus is on explaining variance. Given that I4.0 represents a less mature area of study (Kumar & Bhatia, 2021), PLS is selected as the appropriate analytical method for this research.

Findings

Assessment of the outer (measurement) model

Before examining the structural model, researchers must evaluate the reliability and validity of the research instrument to assess reflective measurement models in PLS-SEM. The first step in evaluating reflective outer models is to examine the extent to which the variance of each indicator is explained by its construct, which reflects the reliability of that indicator. To calculate the amount of variance explained, the factor loading must be squared, representing the bivariate correlation between the indicator and its construct. Factor loadings greater than 0.708 are considered adequate, as they indicate that the latent variable explains more than 50% of the indicator's variance (Hair Jr. et al., 2021). When some indicators have loadings below 0.708, researchers should refrain from immediately deleting them; instead, they should first examine how removing the indicator would affect other reliability and validity criteria. Generally, indicators with loadings between 0.40 and 0.708 should only be removed if their deletion results in improvements in reliability and convergent validity beyond the recommended thresholds. Consequently, indicators with weaker loadings may sometimes be retained in the model (Hair Jr. et al., 2021). The factor loadings and their significance levels are reported in Table 2. In line with the results, the factor loadings are acceptable for all indicators and all questions can be retained in the model. Furthermore, t-values in Table 2 indicate the significance of the factor loadings, confirming that all items were statistically significant, thus demonstrating acceptable reliability for each item.

The next step in evaluating the reflective measurement model involves assessing internal consistency reliability. Internal consistency reliability refers to the degree to which the indicators measuring a construct are correlated. One primary reliability metric in PLS-SEM is composite reliability (Jöreskog, 1971). Values between 0.70 and 0.90 are considered acceptable to good. However, values above 0.90 (and certainly above 0.95) are problematic as they indicate potential redundancy and can attenuate the construct's validity (Diamantopoulos et al., 2012). Cronbach's alpha is another measure of internal consistency reliability, with acceptable thresholds similar to those for composite reliability. Cronbach's alpha provides a conservative, acceptable lower-bound estimate of true internal consistency reliability (Trizano-Hermosilla & Alvarado, 2016). As an alternative, recent research has proposed the exact (or consistent) reliability measure, rho_A (Dijkstra, 2010; Dijkstra & Henseler, 2015). The rho_A coefficient typically lies between the conservative estimate of Cronbach's alpha and the more liberal estimate of composite reliability, thus offering a suitable compromise between these two metrics (Hair Jr. et al., 2021). Therefore, as shown in Table 2, the reliability of the constructs was confirmed.

The third step is to evaluate the convergent validity of each construct. The metric used for this purpose is the Average Variance Extracted (AVE), which is calculated based on all indicators of a construct. The AVE is derived by summing the squared factor loadings and dividing the results by the number of indicators. A minimum acceptable AVE value is 0.50 (Sarstedt et al., 2021). Consequently, based on Table 2, convergent validity was confirmed.

Table 2.
The Results of Reliability and Convergent Validity

Construct	N.O of Items	λ> 0.7	T–Value	α > 0.7	Rho_A > 0.7	CR > 0.7	AVE > 0.5
FI	1-5	[0.609-0.866]	[4.53-9.83]	0.814	0.839	0.869	0.573
I4.0 Tech	6-13	[0.452-0.798]	[2.90-12.23]	0.861	0.885	0.893	0.518
NPDP	14-18	[0.725-0.853]	[12.65-18.65]	0.865	0.867	0.903	0.650
TT	19-22	[0.747-0.919]	[5.39-14.45]	0.856	0.862	0.903	0.701

(Source: The Researcher's Findings)

As shown in Table 2, all constructs demonstrated satisfactory reliability, with composite reliability (CR) values ranging from 0.869 to 0.903 and Cronbach's alpha values ranging from 0.814 to 0.865. The rho_A values also exceeded the 0.70 threshold, confirming internal consistency. Convergent validity was established as all AVE values surpassed the 0.50 criterion (Fornell & Larcker, 1981).

It is worth noting that the FI and I4.0 constructs exhibited some indicator loadings below the ideal 0.708 threshold (FI5: 0.609; I4.0 (3): 0.452; I4.0 (8): 0.452) (see Fig. 3). Following Hair et al. (2021), we retained these items after confirming that their deletion did not improve composite reliability or AVE, and that they contributed to the content validity of the constructs. Specifically, the lowest loading in I4.0 (0.452) relates to "Due to legal requirements/changed legislation," which captures an important external driver of I4.0 adoption that, while less internally consistent with the other items, is theoretically relevant to the SHEA industry context.

Finally, the final stage entails an assessment of discriminant validity, which captures the extent to which a given construct differs from other constructs within the model. According to Fornell and Larcker (1981), cross-loadings typically serve as the first technique for examining the discriminant validity of indicators. As Singh and Anthonysamy (2025) state, an indicator's outer loading on its associated construct must exceed all of its cross-loadings. Table 3 displays the cross-loadings among the indicators and offers insights into the discriminant validity of the constructs. Subsequently, Fornell and Larcker (1981) proposed that discriminant validity is achieved when the square root of each construct's AVE (reported on the diagonal of the Fornell–Larcker matrix) surpasses the correlations between that construct and other constructs in the model (shown in the lower-left portion of the matrix). However, more recent research indicates that this criterion is unsuitable for evaluating discriminant validity, particularly when the factor loadings of indicators within a construct exhibit little variation (for example, when all factor loadings fall between 0.65 and 0.85) (Henseler et al., 2015). Consequently, the Fornell-Larcker criterion is often unreliable and should therefore be avoided (Radomir & Moisescu, 2020). Nevertheless, for researchers' reference, its results are reported in this study. As a superior alternative, discriminant validity assessment using the Heterotrait-Monotrait (HTMT) ratio of correlations has been put forward. Henseler et al. (2015) recommend a conservative acceptability threshold of less than 0.90 (or a more lenient threshold of 0.85) (Henseler et al., 2015). According to Table 3, discriminant validity based on the cross-loadings, the Fornell-Larcker matrix, and the HTMT indices is confirmed.

Table 3.
The Results of Discriminant Validity

Construct	*Fornell and Larcker*				*HTMT*				*Cross Loading*			
	FI	**I4.0 Tech**	**NPDP**	**TT**	**FI**	**I4.0 Tech**	**NPDP**	**TT**	**FI**	**I4.0 Tech**	**NPDP**	**TT**
FI	0.75								[0.60-0.86]	[0.07-0.51]	[0.22-0.49]	[0.31-0.35]
I4.0 Tech	0.40	0.72			0.47				[0.04-0.41]	[0.45-0.79]	[0.25-0.42]	[0.03-0.36]
NPDP	0.64	0.76	0.80		0.70	0.86			[0.42-0.60]	[0.55-0.63]	[0.72-0.85]	[0.28-0.63]
TT	0.59	0.27	0.58	0.83	0.70	0.34	0.66		[0.42-0.60]	[0.10-0.30]	[0.37-0.52]	[0.74-0.91]

(Source: The Researcher's Findings)

Assessment of the inner (structural) model

Following the confirmation of the measurement model's reliability and validity, the researcher proceeds to evaluate the results of the inner model.

The first step in evaluating the inner model involves assessing path coefficients (β) represent the change in the values of an endogenous construct associated with a one standard deviation change in a specific predictor construct. In terms of association, path coefficients typically range between -1 and +1. Coefficients closer to -1 indicate strong negative relationships, while those closer to +1 indicate strong positive relationships.

The significance of these coefficients is crucial and must be examined (Hair Jr. et al., 2021). The path coefficients and their significance are presented in Table 4. According to the results, the effect of FI on NPDP was relatively moderate.

In addition, in testing the inner model, another criterion examines how the removal of a selected predictor construct affects the coefficient of determination of an endogenous construct. This criterion is the effect size (f^2) and is conceptually similar to the magnitude of path coefficients (Hair Jr. et al., 2021). The f2 values of 0.02, 0.15, and 0.35 are considered small, medium, and large effect sizes, respectively (Cohen, 1988). As shown in Table 4, FI's effect size on NPDP was medium.

Table 4.
The Results of Path Coefficients and Effect Size

Hypothesis / Path	Path Coefficient	t-value	Result	f^2
H1: FI -------> NPDP	0.213	3.385	Supported	0.131

(Source: The Researcher's Findings)

The next step is to examine the coefficient of determination (R^2) for the endogenous constructs. The coefficient of determination represents the explained variance in each endogenous construct. It is a measure of the model's explanatory power, also known as in-sample predictive power (Hair Jr. et al., 2021). R^2 values range from 0 to 1, with values closer to 1 indicating stronger explanatory power for the endogenous variable in the model. As a general guideline, R^2 values of 0.66, 0.35, and 0.19 can be considered substantial, moderate, and weak, respectively (Chin, 1998). One limitation of R^2 is its tendency to increase as more explanatory variables are added to the model. Therefore, the adjusted R^2 is viewed as a more conservative estimate (Hair Jr. et al., 2021); however, it is not a precise indicator of the variance explained by an endogenous construct (Sarstedt & Mooi, 2014). According to Table 5, the R^2 and adjusted R^2 values for the endogenous constructs are presented, indicating the model's explanatory power. According to the findings, the research model demonstrates a strong level of predictive power for the endogenous variables.

Table 5.
The Results of R^2 and Adjusted R^2

Endogenous Construct	R^2	R^2 Adjusted	Result (Substantial/Moderate/Weak)
NPDP	0.816	0.801	Substantial

(Source: The Researcher's Findings)

The concept of model fit as known from CB-SEM is not transferable to PLS-SEM because this method follows a different goal when estimating model parameters. Instead, structural model assessment in PLS-SEM focuses on assessing the explanatory and predictive power of the model. Thus, the final step in examining the structural model is to evaluate the model's predictive power using the PLSpredict test. Many researchers interpret the R^2 statistic as an indicator of their model's predictive power. However, this interpretation is not entirely correct, because R^2 only reflects the model's explanatory power within the sample and does not provide information about the model's predictive

power—also referred to as out-of-sample predictive power (Hair Jr. et al., 2021). To examine the model's predictive power, the cross-validated redundancy (Q2) criterion was used. This criterion indicates the degree of variability of the indicators explained by their constructs. The values of this criterion range from -1 to +1, and the closer the value is to +1 within the range of 0 to +1, the higher the quality of the model (Stone, 1974). According to Table 6 it can be concluded that the model based on the Q2 criterion are of appropriate quality. However, the Q2 criterion ignores any input information that the PLS path model provides (Shmueli et al., 2019). For this purpose, researchers introduced PLSpredict, a method for out-of-sample prediction that indicates the model's ability to predict new or future observations (Shmueli et al., 2016). Two criteria, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), have been proposed for this test. In most cases, researchers should use RMSE to assess a model's predictive power. However, if the distribution of prediction errors is highly asymmetric (Danks & Ray, 2018), MAE is considered a more appropriate prediction statistic (Shmueli et al., 2019).

To interpret these criteria, the RMSE (or MAE) values of each indicator should be compared with those of a simple linear regression model (LM). The LM benchmark values are obtained by running a linear regression of each indicator of the dependent construct on the indicators of the exogenous constructs in the PLS path model. When comparing RMSE (or MAE) values with those of the LM, the following guidelines apply (Hair Jr. et al., 2021):

[1] If RMSE (or MAE) values for all indicators are lower than those of the LM benchmark, the model has high predictive power.

[2] If the majority (or an equal number) of indicators produce lower prediction errors than the LM, this indicates moderate predictive power.

[3] If fewer than half of the indicators produce lower prediction errors than the LM, this indicates low predictive power.

[4] If the PLS-SEM analysis does not yield lower prediction errors (in terms of RMSE or MAE) for any indicator compared with the LM, the model has no predictive power.

Based on the normality of the distribution of prediction errors (skewness and kurtosis of prediction errors were within the range of normal distribution), a comparison was made between the RMSE of the PLS-SEM model and the RMSE of the LM-model, which indicated that the model's out-of-sample predictive power was very strong. The results are presented in Table 6.

Table 6.
The Results of Q^2 and PLSpredict

Construct	NPDP1	NPDP2	NPDP3	NPDP4	NPDP5
LM_RMSE	1.130	1.004	1.038	0.913	0.809
PLS–SEM_RMSE	1.048	0.915	1.007	0.869	0.768
Q^2 (for indicators)	0.562	0.613	0.436	0.435	0.494
Q^2 total (NPDP)			0.508		

(Source: The Researcher's Findings)

Moderation analysis

After ensuring that the direct effects of FI are significant, to address the gaps in the literature regarding inconsistent findings, I4.0 technologies and TT were analyzed as moderators. Following the guidelines of Henseler and Chin (2010) and Hair et al. (2021), interaction terms for moderation analysis were constructed using the two-stage approach in PLS-SEM. In Stage 1, the main effects model (FI → NPDP) is estimated to obtain latent variable scores. In Stage 2, the interaction term (I4.0 × FI) is created as the product of the latent variable scores of the predictor (FI) and the moderator (I4.0). The same procedure was applied to the three-way interaction term (TT × I4.0 × FI), where the product of all three standardized latent variable scores was used. The findings revealed that I4.0 technologies play a moderating role in the relationship between FI and NPDP. In addition, the analysis of the moderating effect of TT is significant, confirming that technological turbulence supports the moderating role of I4.0 technologies in the relationship between FI and NPDP. Table 7 shows the findings of the moderating effects.

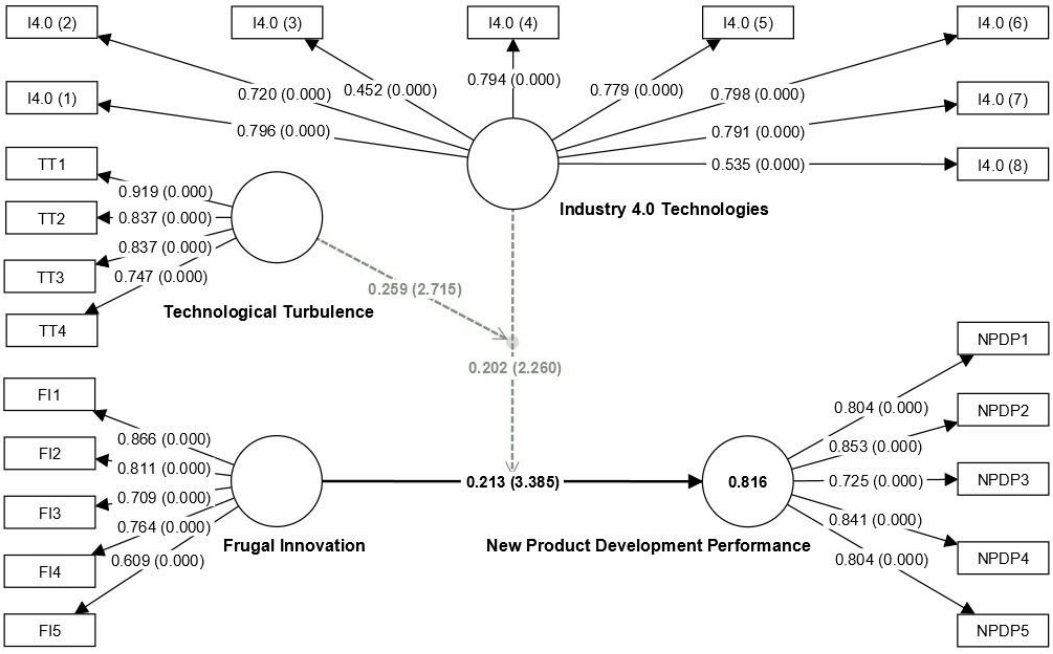
Table 7.
Moderation Effects: Values and Significance

Path (X × M → Y)	Indirect Effect (β)	Significance	Type of Moderation
I4.0 Tech × FI → NPDP	0.202	2.260	Strengthening
TT × I4.0 Tech × FI → NPDP	0.259	2.715	Strengthening

(Source: The Researcher's Findings)

A significant positive coefficient for the interaction term (β = 0.202, p < 0.05 for H2; β = 0.259, p < 0.01 for H3) indicates that the relationship between FI and NPDP strengthens as the level of the moderating variable(s) increases.

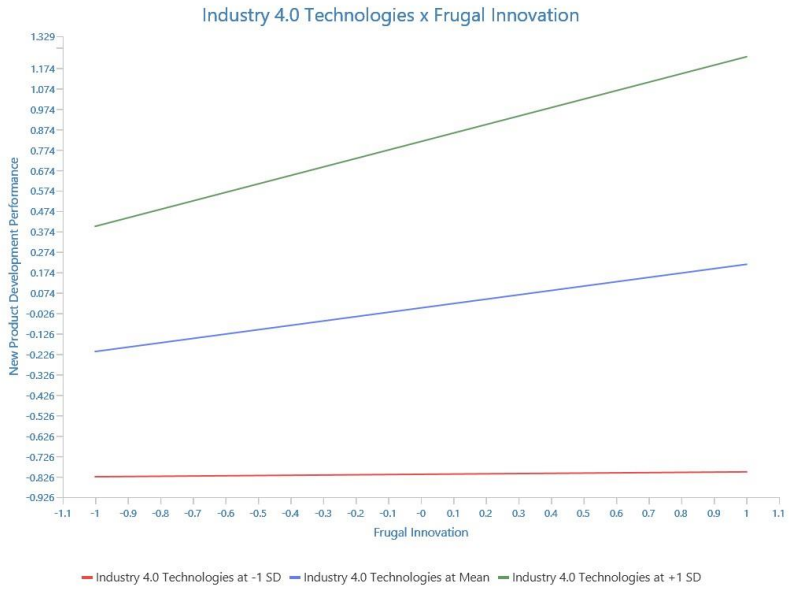
Figure 3.
Path Coefficients



(Source: The Researcher's Findings)

The moderating effect of I4.0 technologies was visualized using the simple slope method, as suggested by Aiken and West (1991). The plot indicates that while FI has a positive and significant effect on NPDP, this relationship is stronger in the presence of a high level of I4.0 technologies compared to a low level of I4.0 technologies (see Figure 4). These results explain the moderating effect of I4.0 technologies and highlight the differences in their impact on NPDP.

Figure 4.
The Moderating Effect of I4.0 Technologies on the Relationship between FI and NPDP



(Source: The Researcher's Findings)

Importance–performance map analysis

Importance-performance analysis map (IPMA) is used to facilitate the interpretation of data and identify the crucial ones requiring managerial focus to allow for optimal and strategic resource allocation. The practicality of IPMA lies in the fact that it examines both the performance and the importance of the attributes in an integrated matrix, given that individual examination might be misleading; a low-performance score might prompt managerial intervention, but if its importance for enhancing satisfaction is low, resources might be better allocated (Teeluckdharry et al., 2024). The goal is to identify antecedents that have a relatively high importance for the target construct (i.e., those that have a strong total effect), but also have a relatively low performance (i.e., low average latent variable scores) (Ringle & Sarstedt, 2016).

Three primary requirements must be checked before carrying out IPMA:

(1) For the rescaling of the latent variables to a range of 0–100, all indicators in the PLS path model should either have a metric scale or an equidistant scale, such as an ordinal scale. Hence, forced-choice scales or nominal scales cannot be used (Sarstedt & Mooi, 2014).

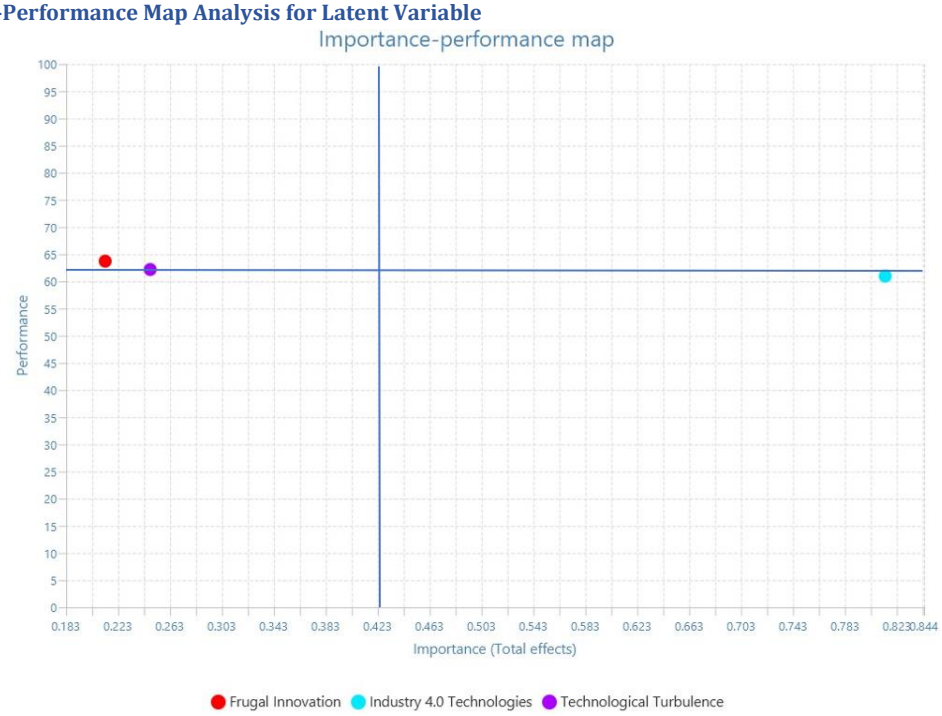
(2) All the indicators must have the same scale direction (Ringle & Sarstedt, 2016).

(3) The values of the outer weight estimates must be positive regardless of the model's

specification (formative, reflective, or higher-order model) (Teeluckdharry et al., 2024).

Given that the necessary preconditions were met, the importance-performance map of the model's latent variables is shown in Figure 5.

Figure 5.
Importance–Performance Map Analysis for Latent Variable



(Source: The Researcher's Findings)

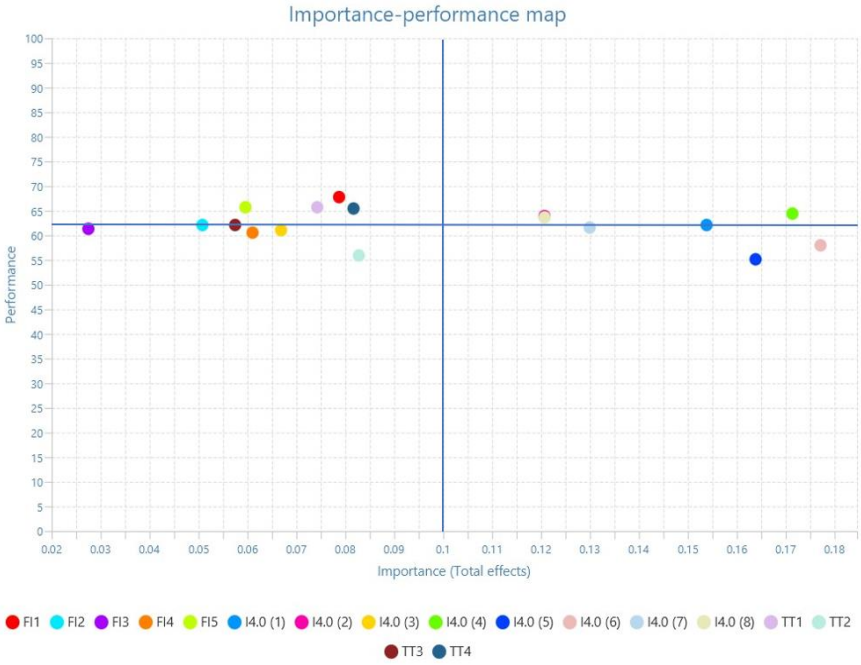
To clarify the IPMA procedure, we followed the guidelines of Ringle and Sarstedt (2016). All indicator scores were rescaled to a 0–100 range to ensure comparability. The target construct was NPDP, and the predecessor constructs included FI, I4.0 technologies, and TT. The importance values were derived from the total effects of each predecessor on NPDP in the PLS path model, while the performance values were calculated as the average rescaled latent variable scores. Generally, when analyzing the importance-performance map, constructs in the lower right area (i.e., above-average importance and below-average performance) are of the highest interest for achieving improvement, followed by the higher right, lower left and, finally, the higher left areas. Therefore, among the variables in the model, the use of I4.0 technologies is of the highest importance.

Similarly, the IPMA can be extended to the indicator level to obtain more specific information on the most effective managerial actions. The importance-performance map of the indicators can be seen in Figure 6.

At the indicator level, the IPMA was conducted using the outer weights of each item to identify which specific aspects of the predecessor constructs have the highest importance but the lowest performance. The distinct insight from IPMA, beyond the core moderation results, is that although I4.0 technologies have the highest total effect on

NPDP, their performance score (mean = 52.3 on a 0–100 scale) is notably lower than that of FI (mean = 68.7). This gap signals that managerial efforts should prioritize not merely adopting I4.0 technologies, but specifically addressing the low-performance indicators identified—namely, workforce qualification (item 13: 'Lack of qualified workforce,' performance = 41.2), regulatory compliance (item 12: 'Due to legal requirements/changed legislation,' performance = 44.8), and customer requirement alignment (item 8: 'Customer requirements,' performance = 49.1). Given this granular analysis, managers should focus resources on the bottlenecks that currently limit the effectiveness of I4.0 adoption; otherwise, they may mistakenly allocate resources to high-performing areas that are already adequate.

Figure 6.
Importance–Performance Map Analysis for Indicators



(Source: The Researcher's Findings)

Control variable: product type

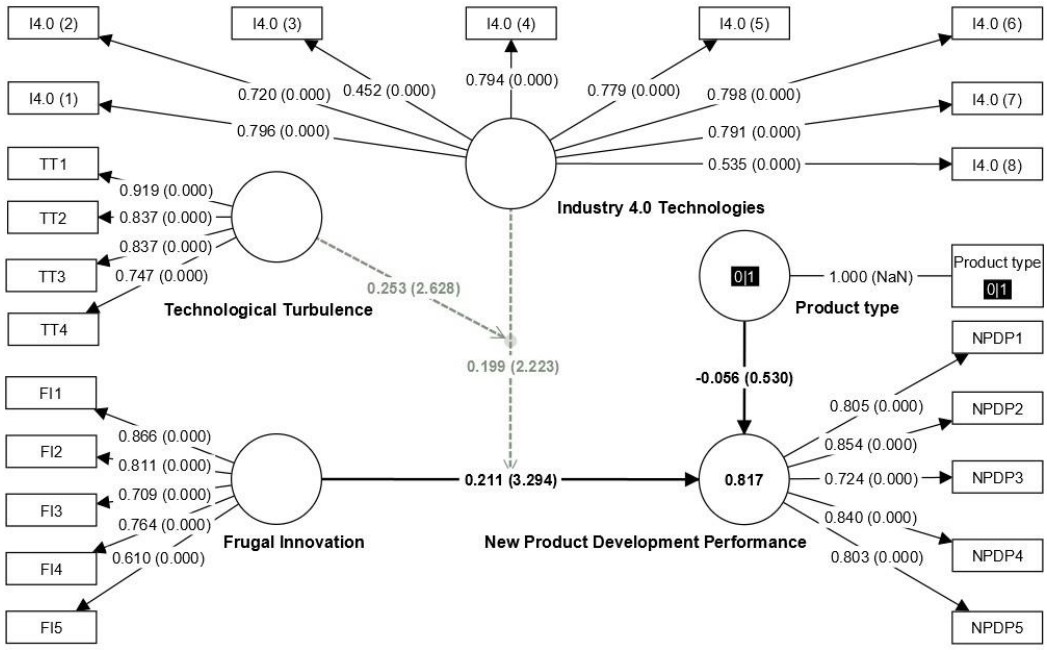
In addition to evaluating the direct and moderating effects, product type was included as a control variable, and its influence was assessed. It should be noted that the study did not focus on the control variable itself, but solely sought to determine whether product type could affect the tested model. The results are reported in Table 8. Based on these findings, the control variable exerts a negligible influence on NPDP and does not significantly affect the relationships under investigation.

Table 8.
Control Variable

Path coefficients	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Product type	-0.056	-0.050	0.106	0.530	0.596

(Source: The Researcher's Findings)

Figure 7.
Control Variable



(Source: The Researcher's Findings)

Discussion and conclusion

Discussion

This study set out to investigate the influence of FI on NPDP within the SHEA industry, while exploring the moderating roles of I4.0 technologies and TT. Using data collected from senior managers in the Iranian SHEA sector and applying PLS-SEM analysis, the findings provided valuable insights into the complex interplay between innovation paradigms and emerging digital technologies in a dynamic and resource-constrained environment.

The positive and significant effect of FI on NPDP ($\beta = 0.213$, $p < 0.01$) aligns with prior findings by Lim and Fujimoto (2019), who showed that resource–constrained innovation can improve product performance without proportionate cost increases. Ukbaeva et al. (2026) similarly argued that constraints foster creativity in NPD, a view that our results empirically supported. Our study extended these insights by quantifying this effect within the SHEA industry, where import prohibitions intensify competitive pressures. The moderate effect size ($f^2 = 0.131$) indicated that FI explains a meaningful—though not dominant—portion of NPDP variance, underscoring the need to examine moderating conditions. Particularly in the SHEA sector, where domestic manufacturers face import bans and intense competition, FI offered a strategic means to manage cost pressures while meeting quality expectations. FI enabled firms to deliver products that satisfy market needs without high costs and to differentiate their offerings in response to evolving consumer demands.

Regarding the moderating role of I4.0 ($\beta = 0.202$, $p < 0.05$), our findings align with Kumar and Bhatia (2021), who found that I4.0 adoption amplifies innovation strategy

benefits in manufacturing, and with Ardito et al. (2019), who attributed I4.0's value to improved decision–making and operational precision. However, while prior studies focused on general performance outcomes, ours specifically demonstrated that I4.0 enhances the translation of FI into NPD success. This synergy arises because digital tools—such as IoT, cyber-physical systems, and data analytics—enable more precise engineering, rapid prototyping, and flexible production lines that reduce waste and inefficiency. For SHEA companies, leveraging these I4.0 technologies facilitates the development of frugal products that maintain quality while reducing costs. Thus, digital transformation embedded in I4.0 acts as an amplifier of FI's benefits, enhancing firms' agility and innovation capacity by strengthening the positive impact of FI on NPD performance.

The significant three-way interaction (TT × I4.0 × FI; $\beta = 0.259$, $p < 0.01$) provided the most novel contribution of this study. While prior research has examined the individual moderating roles of I4.0 (Stentoft et al., 2021) and TT (Chen et al., 2015) separately, no study, to our knowledge, has empirically validated the conditional nature of I4.0's moderating effect across different levels of environmental dynamism. This finding extends Schumpeterian theory by showing that the value of digital capabilities for FI is not uniform but depends on the rate of technological change. Compared with studies in stable contexts (e.g., Wijewardhana et al., 2021), our results suggested that the synergy between FI and I4.0 becomes increasingly critical as TT rises. In highly turbulent environments characterized by rapid and unpredictable technological shifts, the adoption of I4.0 tools becomes even more crucial. Turbulence compels firms to reconfigure resources and update processes continuously; those equipped with advanced digital capabilities are better positioned to anticipate and respond to changes, accelerating innovation cycles and adapting products to emerging trends. This dynamic responsiveness amplifies the combined effect of I4.0 and FI on NPDP, underscoring the importance of technological readiness in volatile markets.

The IPMA further emphasized the managerial priority of investing in I4.0 adoption. Despite its critical role, performance levels in this area lag behind its importance, suggesting room for improvement. Key managerial concerns such as workforce qualification, compliance with changing regulations, and alignment with customer requirements emerged as focal points for strategic attention.

Conclusion

In sum, this research affirmed the strategic value of FI in enhancing NPDP within the resource-constrained and competitive environment of the SHEA industry. It demonstrated that the adoption of I4.0 technologies not only complements but also significantly amplifies the benefits of FI by enabling smarter, faster, and more cost-effective innovation processes. Furthermore, TT acted as a catalyst, heightening the importance of digital readiness and organizational agility in sustaining innovation performance.

For managers and policymakers, the findings underscored the imperative of integrating FI principles with digital transformation initiatives to foster resilient and

competitive enterprises. By focusing on workforce development, regulatory adaptation, and continuous technological upgrading, firms can better navigate the challenges posed by rapidly evolving markets and technological landscapes.

Ultimately, this study contributed to both theory and practice by elucidating the complex mechanisms through which innovation paradigms and emerging technologies interact to drive superior NPD outcomes. It offers a foundation for further scholarly inquiry and practical action aimed at sustaining growth and competitiveness in the modern industrial era.

Theoretical implications

This study makes three distinct theoretical contributions First, it extends RBV by demonstrating that FI functions as a strategic capability whose performance impact is contingent on complementary digital resources. While Barney (1991) argued that valuable, rare, and inimitable resources drive competitive advantages, our findings showed that translating such resources into performance outcomes depends on the presence of complementary technological capabilities (I4.0). This introduces a conditional logic to RBV that moves beyond resource possession toward resource orchestration.

Second, the study advanced the HOT readiness framework by empirically validating I4.0 as a synergistic enabler rather than a direct performance driver. Prior applications of HOT (Yusof et al., 2008) have focused on technology adoption outcomes. Our study shifts the focus to how technology readiness moderates the effectiveness of other strategic initiatives—specifically FI—thereby repositioning I4.0 from a stand-alone investment to a contextual amplifier of innovation capabilities.

Third, the moderated-moderation finding enriched Schumpeterian innovation theory by specifying the boundary conditions under which creative destruction unfolds in resource-constrained settings. Schumpeter (1912/2002) emphasized that innovation disrupts equilibrium, but our results suggest that the disruptive potential of FI is amplified when combined with digital capabilities and environmental turbulence. This adds a nuanced layer to Schumpeterian theory by showing that the pace and impact of innovation-driven disruption are themselves contingent upon technological readiness and environmental dynamism.

All in all, these contributions move the literature beyond bivariate associations toward a more nuanced understanding of how innovation paradigms, digital technologies, and environmental conditions interact to shape NPD outcomes.

Managerial and practical implications for the SHEA industry

We offer the following operational guidelines based on the findings of the hypotheses:

For FI Implementation: Create cross-functional innovation teams tasked with identifying key customer needs and essential product features, optimizing cost without compromising quality or durability. This approach aligns with the value-conscious consumer base typical of the SHEA market.

For I4.0 Integration: Establish pilot projects to deploy Industry 4.0 technologies in

core manufacturing processes, such as smart assembly lines or predictive maintenance systems. Use these projects to build internal expertise and demonstrate tangible improvements in prototyping speed and production efficiency.

For Handling TT: Implement continuous environmental scanning practices to monitor emerging technologies and competitor actions. This will enable timely adjustments to product development strategies and resource allocation.

Based on the IPMA findings:

First, regarding investment in I4.0, the IPMA revealed that 'Lack of qualified workforce' (performance = 41.2) is the most critical bottleneck. Managers should prioritize establishing partnerships with technical universities to create apprenticeship programs specifically focused on digital manufacturing skills for the SHEA sector. A concrete action would be to allocate a portion of the annual R&D budget to a 'Digital Skills Pipeline' initiative, aiming to train the production workforce within 12 months.

Second, concerning regulatory compliance ('Due to legal requirements/changed legislation,' performance = 44.8), firms should designate a compliance officer whose sole responsibility is to monitor regulatory changes and assess their implications for I4.0 implementation. This role should report directly to the CEO and participate in all strategic NPD meetings to ensure that regulatory shifts are translated into timely technological adjustments.

Third, for customer requirement alignment (performance = 49.1), firms should implement a structured feedback loop whereby customer data from smart products (e.g., usage patterns collected via IoT sensors) is systematically analyzed and fed into the frugal design process on a quarterly basis. This ensures that cost-reduction efforts do not inadvertently eliminate features that customers value most.

Fourth, given that TT amplified the value of I4.0, managers in highly turbulent segments of the SHEA market (e.g., smart kitchen appliances) should accelerate their I4.0 adoption timeline to include at least one pilot project within six months, while firms in more stable segments (e.g., basic household tools) can adopt a more gradual pace over 18–24 months. This differential pacing ensures that resource allocation matches the environmental conditions each firm faces.

Limitations and future research directions

While this study provided robust insights, several limitations should be acknowledged. First, the research sample was restricted to senior managers within the Iranian SHEA sector, which may limit the generalizability of the findings to other industries or geographical contexts. Future research could extend this investigation across diverse sectors and regions to validate and expand upon the results.

Second, although the study incorporated key moderating variables, other contextual factors, such as organizational culture, market competition intensity, or government policy support may also influence the relationships and should be explored in future studies.

Additionally, future research could examine the role of specific Industry 4.0 technologies (e.g., artificial intelligence, digital twins, and blockchain) in more detail to

identify which tools most effectively enhance FI outcomes. Exploring the interplay between sustainability-oriented innovation and digital transformation in the SHEA sector represents another promising avenue, given the increasing emphasis on green technologies and the circular economy principles.

Final remarks

This study offered a timely and relevant contribution to innovation management scholarship by elucidating how FI, when combined with I4.0 technologies and adapted to technological turbulence, can significantly enhance NPDP. The insights provided herein equip both scholars and practitioners with a clearer roadmap for navigating the complexities of innovation in today's dynamic and resource–limited industrial landscapes. Embracing this integrated approach will be vital for firms seeking sustainable growth and competitive differentiation in an increasingly volatile global market.

REFERENCE

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Sage publications.

Agarwal, N., & Brem, A. (2012). Frugal and reverse innovation: Literature overview and case study insights from a German MNC in India and China. In *2012 18th International ICE Conference on Engineering, Technology and Innovation* (pp. 1–11). IEEE. https://doi.org/10.1109/ICE.2012.6297683.

Aqmala, D., Panjaitan, R., Ardyan, E., & Putra, F. I. F. S. (2025). The role of green blue ocean strategy in enhancing frugal innovation through IoT and AI: A resource-based view perspective. *Journal of Entrepreneurship, Management & Innovation*, *21*(2), 56–81.

Ardito, L., Petruzzelli, A. M., Panniello, U., & Garavelli, A. C. (2019). Towards industry 4.0: Mapping digital technologies for supply chain management-marketing integration. *Business Process Management Journal*, *25*(2), 323-346.

Awwad, A., & Akroush, D. M. N. (2016). New product development performance success measures: exploratory research. *EuroMed Journal of Business*, *11*(1), 2-29.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99-120.

Bas, C. L. (2020). Frugal innovation as environmental innovation. *International Journal of Technology Management*, *83*(1-3), 78-96.

Burns, T., & Stalker, G. M. (1961). *The management of innovation*. Tavistock Publications.

Chen, J., Neubaum, D. O., Reilly, R. R., & Lynn, G. S. (2015). The relationship between team autonomy and new product development performance under different levels of technological turbulence. *Journal of Operations Management*, *33*, 83-96.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-336). Psychology Press.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd Ed.). Hillsdale: Erlbaum Associates.

Cooper, S. (2017). *Rethink manufacturing, KPMG. Designing a UK industrial strategy for the age of industry 4.0*. KPMG.

Davari, A., & Rezazadeh, A. (2013). Structural equation modeling with PLS. *Jahad University*, *215*(2), 224.

Danks, N. P., & Ray, S. (2018). Predictions from partial least squares models. In F. Ali, S. M. Rasoolimanesh, & C. Cobanoglu (Eds.), *Applying partial least squares in tourism and hospitality research* (pp. 35–52). Emerald Publishing Limited.

De Silva, R. J., Rupasinghe, T. D., & Apeagyei, P. (2019). A collaborative apparel new product development process model using virtual reality and augmented reality technologies as enablers. *International Journal of Fashion Design, Technology & Education*, *12*(1), 1-11.

Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science*, *40*, 434–449.

Dijkstra, T. K. (2010). Latent variables and indices: Herman Wold's basic design and partial least squares. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares: Concepts, methods and applications* (Vol. II, pp. 23–46). Springer.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly*, *39*(2), 297–316.

Dosi, G., Nelson, R. R., & Winter, S. G. (Eds.). (2000). *The nature and dynamics of organizational capabilities*. Oxford university press.

Dost, M., Pahi, M. H., Magsi, H. B., & Umrani, W. A. (2019). Effects of sources of knowledge on frugal innovation: Moderating role of environmental turbulence. *Journal of Knowledge Management*, *23*(7), 1245-1259.

Duncan, R. B. (1972). Characteristics of organizational environments and perceived environmental uncertainty. *Administrative Science Quarterly*, 313-327.

Fiorini, P. D. C., Jugend, D., Scaliza, J. A. A., Chiappetta Jabbour, C. J., & Latan, H. (2025). Digitalisation of manufacturing and innovation: The role of inbound open innovation and environmental turbulence in enabling Industry 4.0-based innovation. *Production Planning & Control*, *36*(13), 1713-1732.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Fransisca, L., Renaldo, N., Chandra, T., Augustine, Y., & Musa, S. (2025). Digital innovation capability and customer value co-creation on new product performance with digital transformation maturity as a moderating variable in trading companies in Indonesia. *Luxury: Landscape of Business Administration*, *3*(1), 1-15.

Iqbal, Q., & Piwowar-Sulej, K. (2023). Frugal innovation embedded in business and political ties: transformational versus sustainable leadership. *Asian Business & Management*, *22*(5), 2225-2248.

Iqbal, Q., Piwowar-Sulej, K., & Kallmuenzer, A. (2025). Sustainable development through frugal innovation: the role of leadership, entrepreneurial bricolage and knowledge diversity. *Review of Managerial Science*, *19*(2), 573-594.

Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbo*ok. Springer Nature.

He, X., & Wu, X. (2024). Social networks and ambidextrous innovation in SMEs: The mediating role of dynamic capabilities and the moderating role of technological turbulence. *Technology Analysis & Strategic Management*, *36*(10), 2662-2675.

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling*, *17*(1), 82-109.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135.

Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: antecedents and consequences. *Journal of Marketing*, *57*(3), 53-70.

Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika*, *36*(4), 409–426.

Knorringa, P., Peša, I., Leliveld, A., & Van Beers, C. (2016). Frugal innovation and development: aides or adversaries?. *The European Journal of Development Research*, *28*(2), 143-153.

Kumar, S., & Bhatia, M. S. (2021). Environmental dynamism, industry 4.0 and performance: Mediating role of organizational and technological factors. *Industrial Marketing Management*, *95*, 54-64.

Knudsen, M. P., Von Zedtwitz, M., Griffin, A., & Barczak, G. (2023). Best practices in new product development and innovation: Results from PDMA's 2021 global survey. *Journal of Product Innovation Management*, *40*(3), 257-275.

Li, C., Murad, M., Ashraf, S. F., & Jiatong, W. (2024). Leadership styles, team innovative behavior, and new green product development performance. *Management Decision*, *62*(10), 3208-3234.

Lim, C., & Fujimoto, T. (2019). Frugal innovation and design changes expanding the cost-performance frontier: A Schumpeterian approach. *Research Policy*, *48*(4), 1016-1029.

Lim, C., Lee, J. H., Sonthikorn, P., & Vongbunyong, S. (2020). Frugal innovation and leapfrogging innovation approach to the industry 4.0 challenge for a developing country. *Asian Journal of Technology Innovation*, *29*(1), 87-108.

Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 1-47.

Obradović, T., Vlačić, B., & Dabić, M. (2021). Open innovation in the manufacturing industry: A review and research agenda. *Technovation*, *102*, 102221.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Qin, W. (2024). How to unleash frugal innovation through internet of things and artificial intelligence: Moderating role of entrepreneurial knowledge and future challenges. *Technological Forecasting & Social Change*, *202*, 123286.

Radomir, L., & Moisescu, O. I. (2020). Discriminant validity of the customer-based corporate reputation scale: Some causes for concern. *Journal of Product & Brand Management*, *29*(4), 457–469.

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems*, *116*(9), 1865-1886.

Rosca, E., Reedy, J., & Bendul, J. C. (2018). Does frugal innovation enable sustainable development? A systematic literature review. *The European Journal of Development Research*, *30*(1), 136-157.

Safardoust, A., Pourqasem Sostani, M., & Salami, R. (2023). Identifying strategic components affecting the position of small home appliance industry. *Journal of Strategic Management Studies*, *14*(53), 1-24.

Sarstedt, M., Bengart, P., Shaltoni, A. M., & Lehmann, S. (2018). The use of sampling methods in advertising research: A gap between theory and practice. *International Journal of Advertising*, *37*(4), 650-663.

Sarstedt, M., & Mooi, E. (2014). *A concise guide to market research: The process, data, and methods using IBM SPSS Statistics* (2nd ed.). Springer.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. E. Vomberg (Eds.), *Handbook of market research* (pp. 587–632). Springer.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.

Sinaga, O., Saudi, M. H. M., & Roespinoedji, D. (2019). The dynamic nexus of digital evolution, environmental turbulence and environmental performance: A case of high-tech industries in the emerging 4th industrial revolution. *International Journal of Energy Economics and Policy*, *9*(6), 386-393.

Singh, P., & Anthonysamy, L. (2025). Development and validation of an instrument to assess instructors' usage, acceptance, and confidence towards ChatGPT: a reliability and

discriminant validity analysis. *Education and Information Technologies*, *30*(17), 25251-25271.

Schumacher, E. F. (1973). *Small is beautiful: Economics as if people mattered*. Blond & Briggs.

Schumpeter, J. A. (1912/2002). The economy as a whole: Schumpeter's lost seventh chapter to "The Theory of Economic Development." *Industry and Innovation*, *9*(1/2), 91–145.

Shmueli, G., Ray, S., Estrada, J. M. V., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of business Research*, *69*(10), 4552-4564.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322-2347.

Song, M., & Montoya-Weiss, M. M. (2001). The effect of perceived technological uncertainty on Japanese new product development. *Academy of Management Journal*, *44*(1), 61-80.

Stentoft, J., & Rajkumar, C. (2020). The relevance of Industry 4.0 and its relationship with moving manufacturing out, back and staying at home. *International Journal of Production Research*, *58*(10), 2953-2973.

Stentoft, J., Adsbøll Wickstrøm, K., Philipsen, K., & Haug, A. (2021). Drivers and barriers for Industry 4.0 readiness and practice: empirical evidence from small and medium-sized manufacturers. *Production Planning & Control*, *32*(10), 811-828.

Stone, M. (1974). Cross-validation and multinomial prediction. *Biometrika*, 509-515.

Teeluckdharry, N. B., Teeroovengadum, V., & Seebaluck, A. K. (2024). A roadmap for the application of PLS-SEM and IPMA for effective service quality improvements. *The TQM Journal*, *36*(5), 1300-1345.

Tiedemann, F., Johansson, E., & Gosling, J. (2020). Structuring a new product development process portfolio using decoupling thinking. *Production Planning & Control*, *31*(1), 38-59.

Trizano-Hermosilla, I., & Alvarado, J. M. (2016). Best alternatives to Cronbach's alpha reliability in realistic conditions: congeneric and asymmetrical measurements. *Frontiers in Psychology*, *7*, 769.

Tsai, K. H., & Yang, S. Y. (2013). Firm innovativeness and business performance: The joint moderating effects of market turbulence and competition. *Industrial Marketing Management*, *42*(8), 1279-1294.

Vesci, M., Feola, R., Parente, R., & Radjou, N. (2021). How to save the world during a pandemic event. A case study of frugal innovation. *R&D Management*, *51*(4), 352-363.

Weyrauch, T., & Herstatt, C. (2017). What is frugal innovation? Three defining criteria. *Journal of Frugal Innovation*, *2*(1), 1–17.

Wijewardhana, G. E. H., Weerabahu, S. K., Nanayakkara, J. L. D., & Samaranayake, P. (2021). New product development process in apparel industry using Industry 4.0 technologies. *International Journal of Productivity and Performance Management*, *70*(8), 2352-2373.

Wu, S., Levitas, E., & Priem, R. L. (2005). CEO tenure and company invention under differing levels of technological dynamism. *Academy of management Journal*, *48*(5), 859-873.

Ukbaeva, Z., Wöllner, T., & Bican, P. M. (2026). Constraints and frugal innovation: Enabling sustainable production through the new product development process. *Sustainable Development*, *34*, 1392-1413.

United Nations. (2015). Transforming Our World: the 2030 agenda for sustainable development. (A/RES/70/1). United Nations: Retrieved from: https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf.

Yadlapalli, A., Rahman, S., & Gunasekaran, A. (2018). Socially responsible governance mechanisms for manufacturing firms in apparel supply chains. *International Journal of Production Economics*, *196*, 135-149.

Yusof, M. M., Papazafeiropoulou, A., Paul, R. J., & Stergioulas, L. K. (2008). Investigating evaluation frameworks for health information systems. *International Journal of Medical Informatics*, *77*(6), 377-385.